Data Center Peak Electrical Demand Forecasting: A Multi-Feature SARIMA-LSTM Model

Zeyu Yang
School of Data Science, The Chinese University of Hong Kong, Shenzhen, Guangdong, China
zeyuyang1@link.cuhk.edu.cn

Chenye Wu
School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, Guangdong, China
chenyewu@yeah.net

Guanchi Liu
Tencent Inc., Shenzhen, Guangdong, China
guanchil13@outlook.com

Jiasheng Zhang
Tsinghua University, Beijing, China
jiashengzhang17@outlook.com

ABSTRACT

Accurate peak electrical demand forecasting plays a pivotal role in managing energy consumption in Internet Data Centers (IDCs), where electricity expense forms a major part of operational costs. To intelligently schedule energy storage for shaving the peak load and reducing both energy expense during peak hours as well as the demand charge, IDC operators need precise predictions of the magnitude and timing of daily peak electrical demand. This paper introduces a novel method for peak load forecasting that combines the strengths of both the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM) models. Our approach is rigorously validated with the field dataset from three Tencent Inc.'s data center in North China region. The successful application of this method underscores its robustness and potential for broader application within the IDC sector and the wider power industry.

CCS CONCEPTS

• **General and reference** → *Performance.*

KEYWORDS

Load forecasting, data center, long short-term memory

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1 INTRODUCTION

Peak electrical demand forecasting is vital to power management in Internet Data Centers (IDCs) under the two-part pricing mechanism for most IDCs, including the time-of-use (ToU) energy tariff and the demand charge. IDC operators continually seek ways to optimize their energy use to reduce the significant operational costs attributed to electricity, including deploying energy storage devices. By deploying energy storage devices, IDC operators can manage their power consumption wisely by storing energy during off-peak tariff periods and discharging during peak tariff periods. The peak-shaving scheduling strategy of storage could help reduce the electricity cost from two aspects including the energy tariff and the demand tariff. The energy tariff is charged based on time-of-use (TOU) pricing mechanism, while the demand charge is determined by the peak electrical demand of IDC. The more energy consumed during the off-peak time and the lower peak demand is, the less the overall electricity consumption would cost. In this light, accurate prediction of the magnitude and timing of daily electricity demand is the prerequisite of intelligent storage scheduling, which is a time series forecasting problem[11]. This paper focuses on this crucial aspect within IDCs, proposing an effective methodology to enhance forecasting accuracy amid the rising complexities of power systems.

1.1 Motivation

The rapid economic growth and extensive electrification in modern society have led to a surge in electricity demand, accompanied by the pressing issue of carbon emissions[4]. Accurate peak electrical demand forecasting is crucial for data centers (IDCs) to strategically plan and effectively manage their resources. By precisely predicting peak electricity demand, IDC operators can minimize energy consumption, reduce carbon emissions, and contribute to low-carbon development. Furthermore, through the utilization of coordinated volt-pressure optimization and smart grid technologies, energy management efficiency can be improved, fostering sustainable development in smart grid systems[19].

IDCs' peak electrical demand forecasting falls into the field of time series forecasting. Traditional algorithms such as the Seasonal Autoregressive Integrated Moving Average (SARIMA) used to be powerful tools for time series forecasting, especially for periodic series. However, they are insufficient to handle modern IDCs' electrical demand series since the consumption curves are becoming more volatile and uncertain. Fortunately, machine learning and deep learning models, particularly Long Short-Term Memory (LSTM) model, are increasingly being employed in the field of load forecasting. These networks, capable of handling the short-term memory and training challenges of traditional Recurrent Neural Networks (RNN), show promise in time series prediction tasks, thus suitable for peak electrical demand forecasting.

Despite LSTM's robust forecasting performance, the effectiveness of this approach hinges heavily on the initialization of its weight matrices. This research aims to address this challenge by exploring the appropriate initialization method for LSTM and incorporating additional features such as temperature to enhance the accuracy of peak electrical demand forecasts.

By comparing LSTM with traditional forecasting models and proposing an innovative model leveraging deep learning, our research contributes to the body of knowledge on peak electrical demand forecasting within IDCs. This improved forecasting accuracy and reliability offer IDC operators a potent tool to manage their energy consumption more effectively, consequently reducing operational costs.

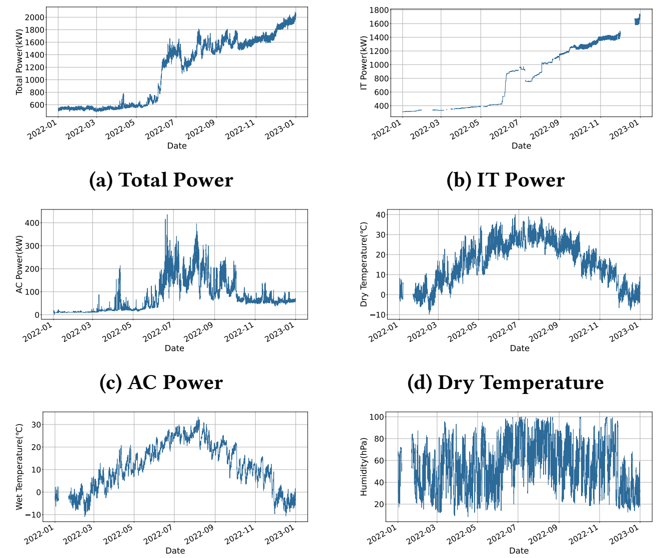
1.2 Related Works

In the context of smart grid and multi-energy vector integration, load forecasting methodologies are facing unique challenges. A study proposed a risk-averse strategy against false data injection attacks in water-energy systems[16]. Concurrently, a two-stage distributionally robust operation model addressed interdependencies in water-energy nexus systems, considering renewable source uncertainties[18]. Furthermore, data-driven methodologies like the Gotcha II system displayed potential for air pollution prediction[20]. Recent work also outlined a two-stage structure to understand the complex interactions in a coupled electricity and carbon market, highlighting the importance of balancing emission allowances and dispatch outcomes for effective emission reduction and market management[15]. Other works have harnessed innovative sensor deployment in vehicles to accurately estimate fine-grained air pollution[6], and a hybrid adaptive particle filter was developed for dynamic air pollution data reconstruction[5]. These advancements have steered us from traditional statistical methods to deep learning, giving rise to our hybrid SARIMA-LSTM model, enhancing peak load forecasting accuracy in the IDC industry.

Load forecasting methodologies have evolved from statistical techniques, such as Goia et al.'s method[8], to more complex models that leverage time-series data. Significant developments include the hybrid neural network model by Amin-Naseri and Soroush[1], albeit limited in handling power demand data non-linearity and uncertainties.

These limitations have catalyzed a shift to deep learning methodologies. LSTM-based models, as used by Choi et al.[7] in energy sustainability monitoring, and Ren et al.[13] in electric vehicle power demand prediction, have proved beneficial. Notably, the impact of international tension on electricity price predictability was studied in the German market, revealing heightened unpredictability despite rising prices[17].

In industrial power demand prediction, Tan et al.[14] proposed a robust hybrid ensemble learning model based on LSTM. Additional research emphasized the influence of job-housing ratio on load pattern variability in the face of urbanization[3].



(a) Total Power **(b) IT Power**

(c) AC Power **(d) Dry Temperature**

(e) Wet Temperature **(f) Humidity**

Figure 1: Sample Features of Module A

Informed by these advancements, our study implements a hybrid SARIMA-LSTM methodology to enhance peak load forecasting in the IDC industry. The unique feature of our model lies in incorporating residuals from LSTM predictions into the SARIMA model. This combination enhances the predictive capabilities of both models, offering a refined approach to peak load forecasting and introducing an innovative perspective to hybrid modeling in this field.

1.3 Our Contributions

The contributions of our study can be encapsulated in the following advancements: Primarily, we introduce a pioneering methodology for IDC peak electrical demand forecasting that combines the predictive prowess of LSTM models with the seasonality-capturing ability of SARIMA. This unique approach adeptly manages the intricacies of time-series data, achieving a heightened level of accuracy in forecasting peak electrical demand. Furthermore, we have integrated and define the critical features combination in IDC peak load forecasting, such as wet temperature, dry temperature, humidity, air conditioning (AC) power, and IT power into our model, thereby enhancing the precision of peak occurrence time predictions under the specific application scenario in IDC. Secondarily, our research validates the proposed methodology by utilizing an unparalleled, annual electrical load dataset derived from three different modules in different IDCs located in North China region, courtesy of the large-scale internet corporation, Tencent Inc. Applying our methodology to this real historical dataset not only substantiates its practicality and adaptivity but also unravels distinctive characteristics inherent in data center power demands. Such insights hold invaluable potential for energy management within data centers. In summary, our study proffers significant strides in the domain of peak electrical demand forecasting methodologies, thereby providing practical guidance for IDC operators intent on bolstering their energy management strategies and mitigating operational expenditures.

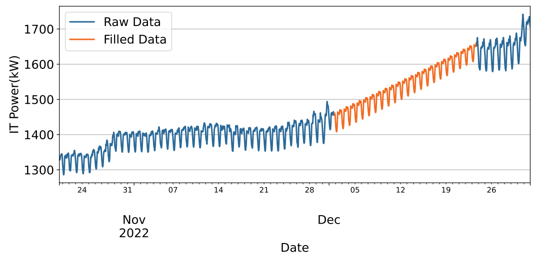


Figure 2: An Example of Missing Value Imputation

2 OVERVIEW OF DATASETS

We were granted access to three unique datasets including Modules A, B, and C, all emanating from data centers located in North China, generously provided by Tencent Inc. Initially, we delve into an elaborate description of Module A's dataset, as it serves as our primary training module for the proposed forecasting model. Modules B and C, while possessing similar characteristics to Module A, are presented subsequently.

Our study's principal objective is to train the forecasting model using Module A, thereby determining the optimal amalgamation of model features. The universality and transferability of our model are then validated utilizing the data from Modules B and C.

Ultimately, we exhibit the results of our model's performance on each of these three datasets separately, thereby underlining the robustness of our methodology and its capacity for effective transferability across diverse data scenarios.

2.1 Data Features

Transitioning from the necessity of electrical demand forecasting, we delve into the critical features used for our data modeling. Module A, consisting of 8760 hourly data entries, forms the basis of our study. Recognizing the significant impact of various variables on power demand, we have incorporated environmental and temporal data, such as temperature, humidity, the hour of the day, day of the week, and month of the year, and socioeconomic variables, including population metrics, air conditioning system details, and building structure specifics, into our model as features[12]. Figure 1 visualizes the data.

2.2 Preprocessing of the Data

Upon accessing the datasets, we identified issues within the raw data, notably the presence of missing values. This necessitated preliminary data preprocessing before the implementation of our forecasting model. Our workflow involves handling missing values, normalizing data, extracting features, and partitioning the dataset. The upcoming sections provide a detailed account of this methodology.

2.2.1 Data Imputation. In our data cleaning process, we removed around 4% of the total dataset where the data for Wet temperature, Dry temperature, and humidity were extensively missing. The insufficient historical data and its continuous nature in this segment made it unfeasible to use time series models for imputation.

Our next step was to address the scattered missing data in the 'Total Power' variable. For this, we employed the Holt-Winters model due to its effectiveness in handling such scenarios[2]. The model's significant access to 8760 data points allows it to capture long-term trends, seasonal variations, and daily patterns in power demand.

The fine-tuned Holt-Winters model demonstrated good performance in predicting IT Power, AC Power, Wet temperature, Dry temperature, and Humidity, with respective RMSEs of 3.73, 13.10, 0.58, 0.64, and 4.16. Figure 2 shows the results of missing value imputation using the Holt-Winters method. As such, we used it to impute missing values for these attributes. However, for the initial 50% of the IT Power data, which lacked distinct time-series characteristics, we used linear interpolation to fill in the missing values.

2.2.2 Data Normalization. We normalize the data by Min-Max normalization. We transform all data into numbers in a range from 0 to 1. We conduct normalization by:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \quad (1)$$

where x is the original data, $x_{\min}$ is the minimum value of the data, x_max is the maximum value of the data, and x' is the normalized data. This transformation can help to mitigate the effect of the disparity in the range of the features and help some algorithms to converge faster.

2.2.3 Feature Extraction. Our research focuses on extracting features from time-series data that are relevant to peak load forecasting in power grids. Understanding the peaks in electricity demand is crucial for the efficient operation of power systems. Therefore, we have selected features that capture both cyclic and seasonal variations in power demand.

We extracted the 'day of the week' feature to account for the fluctuation in electricity demand between weekdays and weekends. Additionally, we considered the 'day of the month' feature to capture cyclic variations within a month. Finally, we included the "month" feature to better understand and predict seasonal variations in power demand.

2.2.4 Data Splitting. In our study, we adopted a 75%:15%:10% split for the training set, validation set, and test set. The training set, which accounted for 75% of the total data, was used to train our LSTM model. The validation set, comprising 15% of the data, was employed during the model training process to fine-tune the parameters and prevent overfitting. The remaining 10% of the data was designated as the test set, serving to provide an unbiased evaluation of the final model.

3 METHODOLOGY

In this research, we utilize a multivariate time series forecasting model, integrating SARIMA and LSTM to predict peak electrical demand. Hence, this section provides an overview of the key methodologies applied in our model, furnishing essential background knowledge for better understanding.

3.1 LSTM Model

The LSTM is a special kind of RNN designed to overcome the vanishing gradient problem in traditional RNNs when dealing with

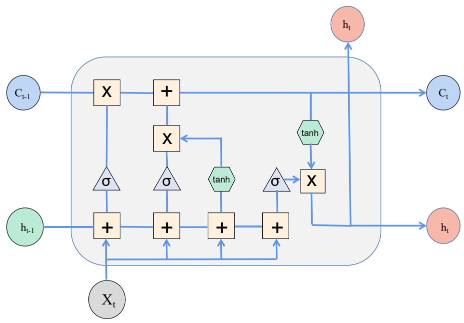


Figure 3: A Memory Cell of LSTM

long sequence data [10]. The LSTM does this through the introduction of 'gates' (input gate, forget gate, and output gate) that allow the network to decide when to forget old information, when to update with new information, and when to output the current state. The core of LSTM is the memory cell, which can store state information for a long duration. Figure 3 explains how the LSTM cell works. The formulas are:

$$
\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \\
C_t &= f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \\
h_t &= o_t * \tanh(C_t),
\end{aligned}
$$

where σ denotes the sigmoid activation function, tanh is the hyperbolic tangent activation function, operator $*$ denotes element-wise multiplication, and $[h_{t-1}, x_t]$ is the vector concatenating h_{t-1} and x_t. The weights (W) and biases (b) for each gate are learned during the training process. In the multivariate scenario, we use LSTM to handle multiple time series inputs, such as temperature, humidity, etc., which may affect the peak electrical demand.

3.2 SARIMA Model

The SARIMA model is an extension of the Autoregressive Integrated Moving Average(ARIMA) model that takes into account seasonality [9]. SARIMA models the seasonality by applying an ARIMA model to lags that are integer multiples of the seasonality. Once the seasonality is modeled, an ARIMA model is applied to the residual to capture the non-seasonal structure.

Specifically, suppose we have a time series y_t with seasonality s. We can attempt to eliminate the seasonality with differencing, by applying the differencing operator Δ_s^D to take the seasonal differences of the time series. Here s is the number of time lags comprising one full period of seasonality. D has a similar meaning to d in ARIMA models, but applies to seasonal lags. We can then capture any remaining structure by applying an $ARMA(P, Q)$ model to the differenced values, but using seasonal lags. That is, instead of using a regular lag operator L, we use L^s. Parameters P and Q are again seasonal time lags. After any seasonality is removed, we can apply another model $ARIMA(p, d, q)$ to $\Delta_s^D y_t$ by multiplying the seasonal model by the new ARIMA model. This can be represented by the following equation:

$$\Theta(L)^p \theta(L^s)^P \Delta^d \Delta_s^D y_t = \Phi(L)^q \phi(L^s)^Q \Delta^d \Delta_s^D \epsilon_t. \tag{2}$$

3.3 Evaluation Metric

Finally, we evaluate the performance of our model using the Root Mean Square Error (RMSE), a commonly used evaluation metric that measures the average squared differences between the observed actual outturn values and the predicted values. The formula for RMSE is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}, \tag{3}$$

where P_i is the predicted value for the ith observation in the dataset, O_i is the observed value for the ith observation in the dataset, and n is the sample size.

4 CASE STUDIES

To investigate the impact of various input features on the accuracy of our predictive model, we conducted an ablation study. Initially, we designed a series of multivariate models, each integrating unique auxiliary features. Through comprehensive evaluation of these models and varying the auxiliary features, we identified the optimal multivariate LSTM model. To enhance prediction accuracy, we refined the forecasting results using SARIMA, thereby creating a hybrid model. The fusion of these models constituted our case study and ultimately yielded corresponding results.

4.1 Ablation Study

We optimized the model parameters through a grid search process and finally adopted an LSTM model with five layers, a 512-dimensional hidden layer, a learning rate of 0.01, and an Adam optimizer, using 72 historical time steps to predict the "Total Power" variable. In our dataset, nine auxiliary features are incorporated: power consumption of air conditioning and other electronic devices, Wet and Dry Temperature, Humidity, and time-related features including Hour, Day of Week, Day of Month, and Month. To scrutinize their impact, we conducted an ablation study.

Table 1 delineates the RMSE of all models on the test set, the daily peak prediction RMSE, and the prediction error (in hours) for the timing of daily peaks under each distinct feature set. Given that the error for the occurrence time of daily peaks gravitates around 8 hours, an 8-hour corrective measure has been applied to adjust the error.

The results compellingly demonstrate that the integration of features relevant to the power consumption of other devices into the model significantly augments the precision of peak value predictions. Nevertheless, the effectiveness of these features is largely dependent on their interaction with others. Relying exclusively on power consumption-related features does not yield satisfactory results. Comprehensive experiments conducted on data from three separate modules have manifested affirmative results, thereby demonstrating the model's robustness and versatility.

Upon inspection of the tables, it is evident that the RMSE for predicting the specific value of the peak is approximately 0.273 when all features are incorporated, indicating commendable and consistent performance. However, the prediction for the timing of

Table 1: Results of the Ablation Experiment on Module A

Features	Date/Weather	Weather/Power	Date/Power	Full	Date	Weather	Power
Test RMSE	0.766	0.368	0.323	**0.261**	0.314	0.747	0.794
Peak Value RMSE	0.295	0.314	0.192	**0.273**	0.328	0.495	0.834
Peak Time Error	0.089	0.043	0.051	**0.041**	0.031	0.030	0.441

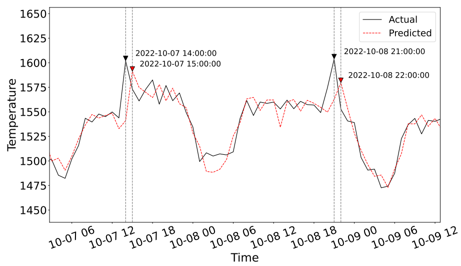


Figure 4: Prediction Performance of Sarima-LSTM Model

the peak shows room for improvement. Interestingly, when only date-related or weather-related features are utilized for prediction, the timing of the peak is forecasted with greater accuracy. Thus, the selection of features can be tailored according to specific application requirements.

4.2 Integrating LSTM Model with SARIMA

Based on the ablation study and prediction performance analysis, it is clear that the integration of relevant features related to power consumption and weather significantly improves the precision of peak value predictions. However, the timing of the peak can be further improved by utilizing specific sets of features. These findings led us to refine our approach and propose an integrated hybrid model combining LSTM and SARIMA models to enhance predictive performance. This approach followed a series of sequential steps:

Initially, we utilized the training dataset to construct and train the LSTM model which considers all the relevant features. The model was then harnessed to generate forecasts for the test set, yielding a set of initial predictions. The residuals, reflecting the discrepancy between the LSTM forecasts and the actual values, were subsequently computed. In the next phase, we harnessed these residuals to train a SARIMA model. This model was leveraged to predict the prospective residuals. The final predictions were generated by amalgamating the SARIMA-predicted residuals with the initial LSTM forecasts. This elegant integration yielded refined forecasts, optimizing the predictive capabilities of our model.

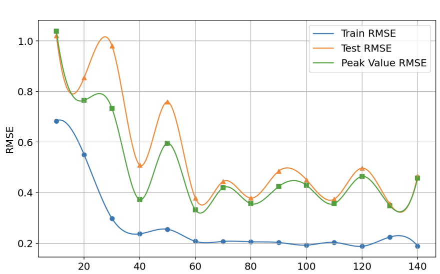


Figure 5: Learning Curve

Table 2: Comparison of Predictive Performance between LSTM and LSTM-SARIMA on each Module

	Module A	Module B	Module C
LSTM			
test RMSE	0.261	0.051	0.033
peak value RMSE	0.273	0.024	0.022
peak time error	0.041	0.041	0.019
LSTM+SARIMA			
test RMSE	0.134	0.027	0.025
peak value RMSE	0.163	0.014	0.019
peak time error	0.037	0.059	0.063

Significant improvements were observed in the prediction of peak load. As demonstrated in Table 2, we noted an increase in prediction accuracy for both the load and peak load values.

While the overall performance of the combined model was commendable, there was a minor deviation in predicting the timing of peak load occurrences. However, considering the context and the overall objectives of the analysis, this discrepancy remains relatively small and may not significantly impact the usefulness of the model's predictions. To provide a visual representation of the partial prediction performance, Figure 4 illustrates the model's predictions compared to the actual values. The analysis of these results aids in understanding the model's strengths and limitations, enabling further refinement if necessary. Additionally, an analysis of the observed learning rate curve, as depicted in Figure 5, revealed that the model's optimal prediction performance was generally attained around 80 epochs. Therefore, during the application, the training iteration should ideally be halted between 80 to 90 epochs. Continuing training beyond this point would only consume more computational resources without enhancing the model's generalization ability.

5 CONCLUSION

We propose a novel approach for peak load forecasting in data centers that combines the strengths of SARIMA and LSTM models to significantly enhance prediction accuracy. By forecasting the residuals of LSTM predictions with SARIMA and implementing subsequent adjustments, we substantially improve the prediction accuracy. Experimental evidence affirms the superior performance of our model in peak load forecasting, providing data center proprietors with a potent tool for strategic decision-making, ultimately facilitating cost savings. Our model could also find potential use in optimizing energy efficiency within dynamic load management systems.

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